Three simple ideas for predicting progression to Alzheimer's disease

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Predicting the progression of mild cognitive impaired (MCI) subjects to Alzheimer's disease (AD) is an ongoing challenge. We propose a combination of simple ideas to compare their performance to other sophisticated machine learning approaches.

We present three approaches making use of a public dataset, the Alzheimer's Disease Neuroimaging Initiative (ADNI),

We set a performance baseline using only demographic, genetic and neuropsychological tests as data (gender, education level, APOE4, MMSE, CDR sum of boxes, ADASCog).

When using imaging data, an important finding is that when an SVM is trained for discriminating between cognitive normal (CN) subjects and AD patients, and the resulting classifier is applied to MCI subjects to predict conversion, performance using FDG PET data improves with respect to a classifier trained and tested on the sMCI and pMCI population.

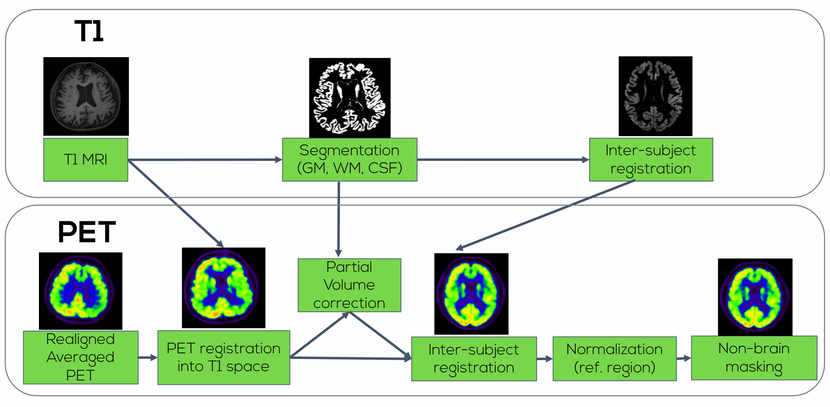
The third approach, consisting of multimodal data, namely the combination of the scores obtained from SVM for T1w and FDG-PET data, and the demographic and clinical data, provided the best prediction results.

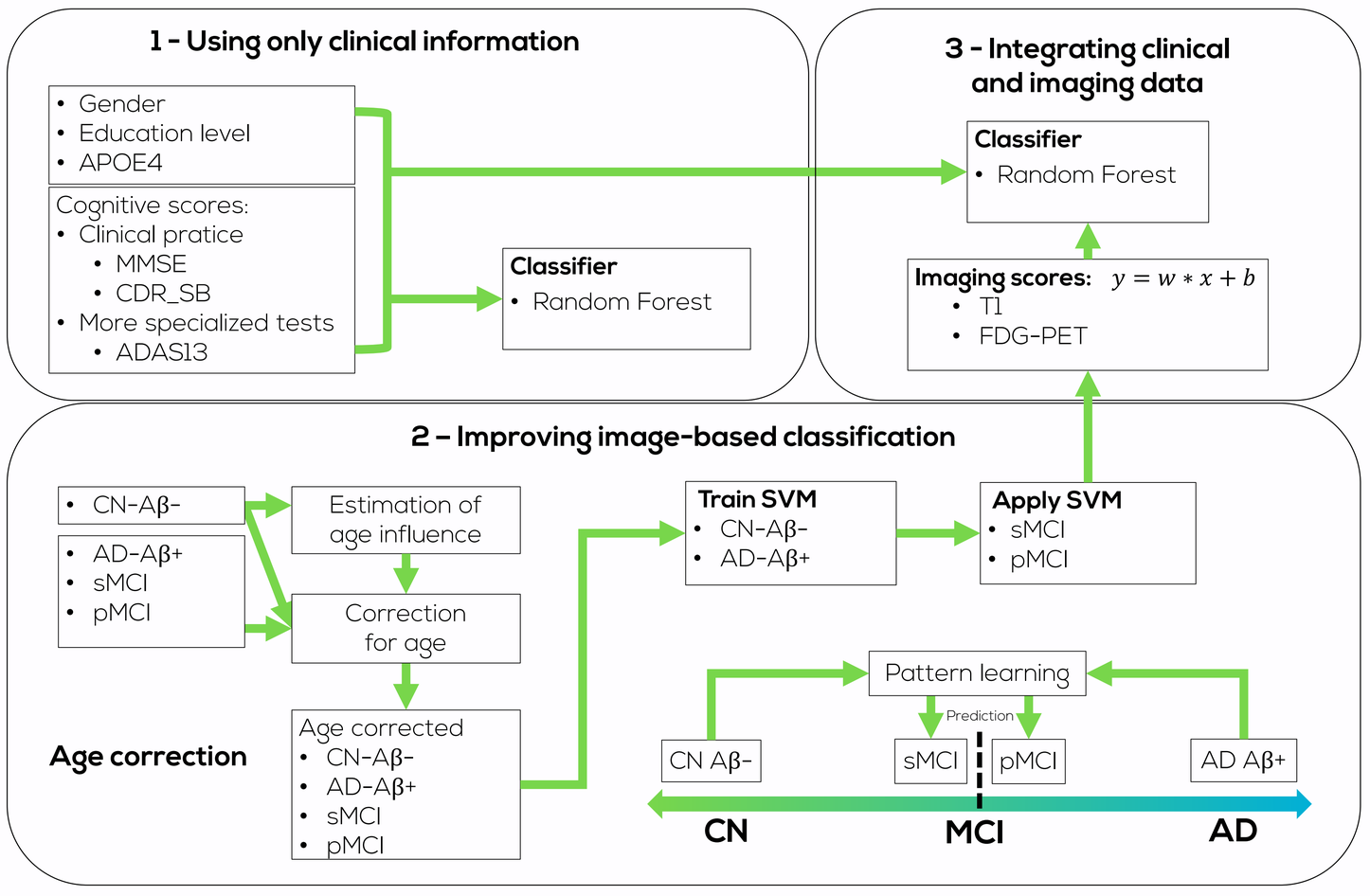
Methods

Clinica software

- **ADNI** dataset conversion to standardized file organization (**BIDS**), including clinical data.
- Tools for obtaining - subjects-sessions lists
  - diagnosis lists
- Complex processing pipelines involving combination of different image analysis software packages
- Integration between feature extraction and statistics / machine learning approaches

Feature extraction pipelines





Results

These ideas were tested on 748 ADNI subjects with T1 MRI and FDG PET data.

They were grouped as:

- CN-Aβ-(111),
- AD-Aβ+(125)
- Stable MCI (309)
- Progressive MCI (164)

MCI to AD progression was determined for subjects followed during at least 36 months. The criterion was if an MCI subject at the baseline progressed, or not, to AD between their first visit and the visit at 36 months.

Features	Classifier	Balanced Accuracy	AUC	Accuracy	Sensitivity	Specificity
Gender, education level, APOE4, MMSE, CDR	Random Forest	0.683	0.754	0.694	0.648	0.718
Gender, education level, APOE4, MMSE, CDR, ADASCog	Random Forest	0.757	0.842	0.766	0.731	0.784
T1w MRI all voxels	Linear SVM	0.67	0.736	0.698	0.586	0.754
FDG PET all voxels	Linear SVM	0.708	0.777	0.732	0.633	0.782
T1w MRI all voxels	Linear SVM (trained on CN Aβ- vs AD Aβ+)	0.679	0.764	0.708	0.547	0.811
FDG PET all voxels	Linear SVM (trained on CN Aβ- vs AD Aβ+)	0.761	0.818	0.788	0.666	0.856
T1 score, FDG score gender, education level, APOE4, MMSE, CDR	Random Forest	0.776	0.854	0.8	0.702	0.849
T1 score, FDG score, gender, education level, APOE4, MMSE, CDR, ADASCog	Random Forest	0.795	0.878	0.815	0.736	0.855

Table 1: Classification results for sMCI vs pMCI task

- Classifications using only socio-demographics, genetics and neuropsychological tests data provide already acceptable accuracy (76%)
- Inclusion of ADASCog test improves prediction
- SVM classifier trained on CN Aβ- vs AD Aβ+ task and applied to predict sMCI vs pMCI performs better (76%) than a classifier trained and tested on the sMCI and pMCI population (71%) for FDG-PET data
- Classification making use of both clinical data and scores from imaging data reaches 80% of balanced accuracy

Conclusion

- It is important to compare new models using brain imaging to those using only clinical data
- Training on simpler CN Aβ- vs AD Aβ+ classification task helps solving more difficult task of sMCI vs pMCI
- Integrating clinical and imaging data improves performance over individual approaches
- Simple classification methods provide a baseline comparable to more sophisticated methods

Downloads

All the code used to generate the results presented in this work is publicly available at: https://gitlab.icm-institute.org/aramislab/AD-ML/PRNI2018